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Heat exposure during outdoor activities in the US varies significantly by city, demography, and activity

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ABSTRACT

Environmental heat is a growing public health concern in cities. Urbanization and global climate change threaten to exacerbate heat as an already significant environmental cause of human morbidity and mortality. Despite increasing risk, very little is known regarding determinants of outdoor urban heat exposure. To provide additional evidence for building community and national-scale resilience to extreme heat, we assess how US outdoor urban heat exposure varies by city, demography, and activity. We estimate outdoor urban heat exposure by pairing individual-level data from the American Time Use Survey (2004–2015) with corresponding meteorological data for 50 of the largest metropolitan statistical areas in the US. We also assess the intersection of activity intensity and heat exposure by pairing metabolic intensities with individual-level time-use data. We model an empirical relationship between demographic indicators and daily heat exposure with controls for spatiotemporal factors. We find higher outdoor heat exposure among the elderly and low-income individuals, and lower outdoor heat exposure in females, young adults, and those identifying as Black race. Traveling, lawn and garden care, and recreation are the most common outdoor activities to contribute to heat exposure. We also find individuals in cities with the most extreme temperatures do not necessarily have the highest outdoor heat exposure. The findings reveal large contrasts in outdoor heat exposure between different cities, demographic groups, and activities. Resolving the interplay between exposure, sensitivity, adaptive capacity, and behavior as determinants of heat-health risk will require advances in observational and modeling tools, especially at the individual scale.

1. Introduction

Cities face warmer futures as a consequence of continued urbanization and global-scale climate change, and health needs related to heat may grow independently of projected warming as urban populations grow and age (McCarthy et al., 2010). Heat already ranks as a leading weather-related cause of human mortality and morbidity in the US (Berko et al., 2014), and improved planning, preparedness, and response strategies are required now and into the coming decades.

The immediate impacts of heat on human health and well-being span a wide range of events and outcomes, including thermal discomfort, fatigue and exhaustion, cardiovascular and respiratory distress, and heat stroke. Beyond these immediate effects, heat has the potential to disrupt other health-promoting activities. In some regions, heat may deter or constrain outdoor physical activity (Obradovich and Fowler, 2017; Zivin and Neidell, 2014), which has been widely linked to physical (Sallis et al., 1998) and mental health benefits (Frumkin et al., 2017). Furthermore, if heat affects how and where people choose to spend their time, downstream impacts on public transportation, tourism, commerce, and other sectors could occur. Thus, there should be wide interest in understanding more precisely the nature of people's experiences with heat in cities, not only to reduce adverse health events, but also to help cities achieve other goals related to economic growth, efficiency, equity, and overall quality of life.

Vulnerability to heat and other hazards is often defined as a function of exposure, sensitivity, and adaptive capacity (Eisenman et al., 2016;

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Turner et al., 2003). Regardless of the specific framing used to define risk or vulnerability, *exposure* is a critical link in the causal pathway that connects environmental heat to societal outcomes of interest. At the population scale, there have been significant advances over the past several decades in understanding how weather conditions contribute to mortality and morbidity in cities (Anderson and Bell, 2009; Eisenman et al., 2016; Gasparrini et al., 2015; Saha et al., 2013). The repeated identification of temperature-mortality and temperature-morbidity associations across the world points to the obvious importance of exposure. Previous literature has widely established the link between lower socioeconomic status and increased risk of negative heat-related health outcomes (Eisenman et al., 2016; Harlan et al., 2013; Pickett and Pearl, 2001; Reid et al., 2009; Uejio et al., 2011). Characteristics such as higher rates of pre-existing health conditions, lower quality housing, less access to cooling resources, and low surrounding vegetation are common determinants of increased risk. Individuals living in poverty have higher rates of pre-existing health conditions (Joseph et al., 2007; Phelan et al., 2010) and decreased ability to access necessary medical care or cooling resources (Balbus and Malina, 2009), leading to increased risk (Kovats and Hajat, 2008). However, the specifics of population heat exposure—necessitating contact between individuals and the environment—has rarely been considered in heat-health risk assessments as it has been in other environmental topics such as pollution exposure (Ott, 1985). Understanding the circumstances by which people are exposed to heat and how this exposure varies at scales ranging from person-to-person to city-to-city may offer new insights into the risk mitigation and adaptation strategies that might be most efficient or beneficial.

Assessment of heat exposure at the individual level can be difficult, and consequently much research focuses on place-based rather than person-based assessments. Personal heat exposure is defined as contact between an individual and an indoor or outdoor environment that poses a risk of thermal discomfort and/or an increase in core body temperature (Kuras et al., 2017). Thus, assessment of personal heat exposure requires not only information about environmental conditions, but also information about people and their time-activity patterns. Although observational and simulation data related to human time-activity patterns are at the core of exposure assessment for other hazards such as air pollutants (Jerrett et al., 2005; Park and Kwan, 2017), such data have infrequently been collected or examined to understand the nature of health risks associated with heat. The research that does exist spans case study approaches using wearable sensors (Bernhard et al., 2015; Kuras et al., 2015); city-scale assessments using simulation tools (Glass et al., 2015; Karner et al., 2015; Swarup et al., 2017), and analysis of national-scale survey data (Obradovich and Fowler, 2017; Zivin and Neidell, 2014). In addition to heat exposure, activity intensity can also influence heat stress; higher physical exertion (i.e. increased metabolic rates) can accelerate heat exhaustion (Armstrong et al., 2007; Havenith et al., 1998). However, heat exposure research lacks quantification of the intensity of physical activity during hot weather despite clear guidelines to avoid high intensity physical activity when heat stress is possible (OSHA, 2017). As a result, there is opportunity to evaluate activity intensity alongside heat exposure to identify if activity intensity is an overlooked factor when evaluating heat exposure.

To address these research gaps, we focus on two main research questions: 1) How does human activity lead to different levels of outdoor heat exposure in the US urban population? and, 2) How does accumulated heat exposure vary amongst population subgroups in US urban areas?

2. Methodology

To evaluate the relationship of heat exposure with activity, urban location, and demography across the contiguous US, individual-level time-activity data from the American Time Use Survey (ATUS, years 2004–2015) are combined with weather data for major metropolitan statistical areas (MSAs) in the US. Heat exposure during activities is assessed using measures of metabolic intensity, activity duration, and regional apparent temperature.

2.1. Activity data

Administered by the Bureau of Labor Statistics (BLS), the ATUS is an annual and ongoing survey that estimates national trends in labor, health, and social activity. Time use data from the ATUS are compiled to identify historical activity patterns in the urban US Individuals age 15 or older are eligible, and questions are asked via computer-assisted telephone interviewing about time use, socioeconomic status, and characteristics of their household (BLS and US Census Bureau, 2016). The survey of respondent's time use encompasses all activities during a pre-determined 24-h date. We choose the ATUS to evaluate individual heat exposure because it comprehensively documents daily personal time use over a long period for many individuals living in different cities. Activity records are temporally explicit, allowing regional temperatures to be matched with each activity to estimate heat exposure for activities that occur outdoors. We focus on aggregation of ATUS records at the MSA level to compare regional patterns in exposure. This is the smallest spatial scale at which sufficient sample sizes exist for a multi-city analysis, allowing for comparisons across activity times and types, demographic groups, and MSAs. The ATUS has been conducted since 2003, but data utilized is from July 2004 to December 2015 due to significant changes in the survey in mid-2004.

To identify geographic locations of activities, ATUS records are matched to records from the Current Population Survey (CPS) to identify the corresponding MSA of residence for each household (Flood et al., 2015). We choose 50 of the most populous MSAs for evaluation such that a high sample of outdoor activities during hot weather across multiple climates could be assessed. Supplementary Information (SI) Tables S1 and S2 summarize the MSAs included, and Fig. 1 displays a US map with climate zone classifications and MSAs locations. We group MSAs according to the US Department of Energy climate zone classifications (Baecheler et al., 2010) to compare urban heat exposure patterns across contiguous US climates. As this classification system is at the county level, we aggregate up to the MSA level. Of the MSAs in this analysis, 12 have inter-county, intra-MSA climate zone classifications. In these cases, the dominant climate zone by population cover is chosen (see SI Table S3 for details).

2.2. Classifying outdoor activities

This analysis focuses on outdoor activity and its associated heat exposure and metabolic intensity. ATUS activity types and location codes were reviewed to determine which activities occur indoors, outdoors, or at an unknown location, following a similar approach to Zivin and Neidell (2014). As this classification scheme is conservative with marking activities as occurring outdoors, actual time spent outdoors by ATUS respondents may be underestimated.

Activities (ATUS variable TRCODEP) are coded as occurring outdoors or elsewhere (inside or unknown) based on the activity description. Activities are coded as occurring indoors or outdoors if they are explicitly described as such or are highly probable to occur indoors ($P_{indoor} \gg P_{outdoor}$) or outdoors ($P_{indoor} \ll P_{outdoor}$). Note that probabilities for these activities to occur indoors or outdoors are not explicit but used as examples for context. For activities that usually occur indoors but may occur outdoors depending on circumstance ($P_{indoor} > P_{outdoor}$), a classification of ‘indoors’ is chosen. For remaining cases, such as activities that could reasonably occur either indoors or outdoors ($P_{indoor} \cong P_{outdoor}$), or locations with vague descriptions, a classification of unknown is chosen. The distinction between indoor activities and activities with an unknown location is trivial for this analysis because only outdoor heat exposure is being investigated, but indoor and unknown activity locations are still differentiated for clarity. Examples of

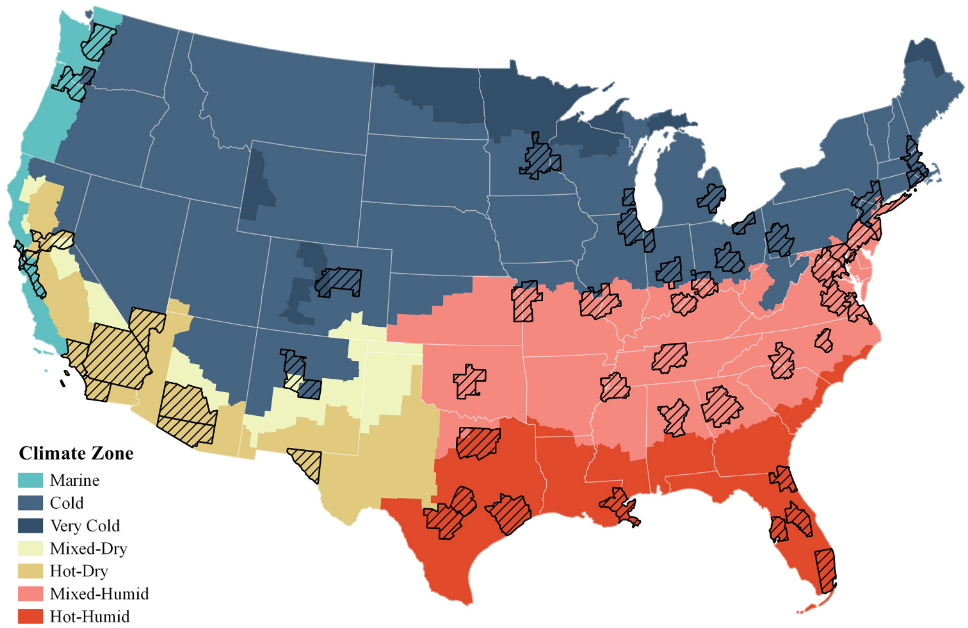

Fig. 1. Metropolitan Statistical Areas studied with climate zones classifications. MSAs included in this analysis are hatched in black. For a list of the MSAs, please see the SI. Note that the 'Very Cold' climate zone is not represented as a dominant climate zone for any MSA studied.

probable indoor activities are "laundry", "bowling", and "computer use;" examples of probable outdoor activities are "exterior [household] cleaning", "hiking," and "golfing;" examples of activities with unknown indoor/outdoor classifications are "traveling", "tobacco and drug use", and "playing basketball". Some examples of activities that are coded as indoors under the assumption the activity usually occurs indoors are "eating and drinking", "watching football", and "playing with children (not sports)." For a full list of how ATUS activities are classified, see SI Section 1.2.

A separate variable, activity *location* (TEWHERE), is also coded as indoors, outdoors, or unknown using the same above classification scheme independent of the activity type. For the given activity locations, only "walking," "biking," "outdoors away from home," and "boat/ferry" are classified as outdoor locations while all other locations are indoors or unknown (e.g. "bus", "library," and "bank" are indoors; "unspecified place" and "other mode of transportation" are unknown). This approach is used so that in cases where the location is unknown based on activity type (e.g. "playing basketball"), the activity can still be marked as indoors or outdoors when the activity location is known (e.g. "outdoors away from home") and vice versa. In cases where the activity type and location have conflicting indoor/outdoor codes, a code of outdoors is assigned. This is done because the coding is conservative in assigning outdoor activities, therefore an outdoors code is assumed dominant (e.g. "eating and drinking" is coded occurring indoors but would be coded outdoors if it occurs "outdoors away from home").

Across all work-related activities, less than half a percent occurred "outdoors away from home," and 72% occurred at "the respondent's workplace," the latter of which does not differentiate between indoor and outdoor presence (and thus, were *not* coded as occurring outdoors in our analysis). Therefore, work-related outdoor heat exposure is likely under captured in the ATUS, and this analysis focuses on non-work related activities.

2.3. Weather data

Weather data are obtained from the US National Centers for Environmental Information for each MSA at hourly and sub-hourly times coincident with the ATUS records. Consistent with other multi-city scale assessments of temperature-health risks, meteorological stations are chosen based on completeness of weather records and proximity to MSA population centers with use of one station per MSA.

Outdoor environmental heat is quantified using apparent temperature (T_A). Apparent temperature is commonly used as a combined temperature-humidity index that is intended to represent thermal stress associated with environmental heat as perceived by a human body (Brooke Anderson et al., 2013; Zanobetti and Schwartz, 2008). T_A is estimated using the National Weather Service (NWS) parameterization of the original Steadman (1979) apparent temperature algorithms (NWS, 2016; Rothfusz, 1990). For more details of apparent temperature estimation via this method, refer to SI Section 2. For each activity record, all T_A observations occurring during an activity are matched based on date, time, and MSA. For activities occurring during times with gaps in weather observations, the nearest weather observation to the activity time is used if the time difference is under three hours apart. For this approach, only 0.31% (n = 210) of outdoor activities have unavailable weather observations within this window, which are omitted.

2.4. Evaluating individual exposure and activity intensity

The NWS heat index ('likeliness of heat disorders with prolonged exposure or strenuous activity') is referenced to evaluate severity of heat exposure for air temperatures above 27 °C (80°F) with relative humidity above 40% (NWS, 2017). Heat risk and recommended preventative measures elevate with the NWS heat index as follows: 27–33 °C T_A (80–91°F T_A) require *caution*; 33–39 °C T_A (91–103°F T_A) require *extreme caution*; and 39 °C + T_A (103°F + T_A) are associated with *danger*. Although there is a fourth heat index threshold indicating *extreme danger* (52 °C T_A and above), it is omitted from this analysis because outdoor activity above 39 °C is rarely captured in the ATUS; out of all outdoor activities, only 0.64% (n = 417) occurred above 39 °C, and no activities were observed above 52 °C. To improve the accuracy of exposure estimates for outdoor activities, outdoor exposure is a time-weighted function of all T_A observations for the duration of each activity.

As high physical exertion increases likelihood of heat stress because of internal heat production, metabolic equivalent of task (MET) data for ATUS activity types estimated by Tudor-Locke et al. (2009) are linked to each activity to assess intensity and exposure simultaneously. One

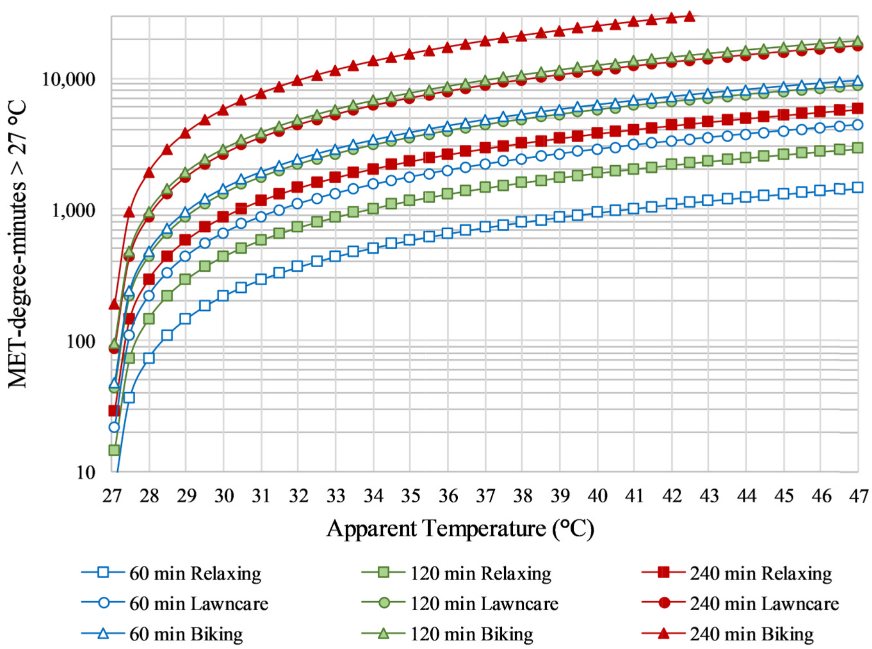

Fig. 2. MET-degree-minutes for sample activities and durations. Note that the y-axis scales logarithmically. Relaxing (full description: relaxing and thinking) is 1.21 MET and represents a low intensity activity. Lawn care (full description: lawn, garden, and houseplant care) is 3.66 MET and represents a medium intensity activity. Biking is 8.0 MET and represents a high intensity activity.

MET is defined as the energy to lie or sit quietly and is equivalent to a metabolic rate of consuming 3.5 mL O_2/kg/minute. For example, "relaxing and thinking" is 1.2 MET, "lawn, garden, and houseplant care" is 3.66 MET, and "biking" is 8.0 MET (see SI Section 1.2 for full details). ATUS activities have a range of 0.9–10.0 MET. As physical exertion, activity duration, and temperature are important factors when considering heat stress, heat exposure is evaluated as both activity intensity-time (MET-minutes) within NWS heat index levels, and as MET-degree-minutes (MDMs) above 27 °C T_A (80°F T_A). Fig. 2 demonstrates how activities of varied intensity and duration translate to exposure intensity (MDMs above 27 °C T_A) as T_A increases.

We evaluate exposure differences between demographic subgroups to determine if previously established at-risk demographics are more likely to accumulate heat exposure. Socioeconomic status has been widely connected to health outcomes (Pickett and Pearl, 2001), and heat-related social vulnerability has been well documented (Eisenman et al., 2016; Harlan et al., 2013; Reid et al., 2009; Uejio et al., 2011). Lower socioeconomic status is linked to higher rates of pre-existing health conditions, lower quality and higher density housing with less tree cover (Iverson and Cook, 2000; Martin et al., 2004), and lower access to air-conditioning and cooling (Fraser et al., 2016; O'Neill et al., 2005), all of which can contribute to increased risk of heat stress (Kovats and Hajat, 2008). To ensure income is consistent across years, income levels are adjusted to $2015 based on the BLS monthly historical Cost Price Index for urban US Consumers (US BLS, 2018). Elderly individuals are often cited as the most vulnerable demographic to heat stress, especially those 65 years of age or older (Gosling et al., 2009; Grundy, 2006; Hondula et al., 2012; Whitman et al., 1997). We therefore define elderly individuals as age 65 and older. Race and heat-related mortality have also been linked in some analyses with those identifying as Black often deemed most at risk (O'Neill et al., 2005; Whitman et al., 1997), indicating race is an important factor to include in assessments of heat exposure.

To identify significant predictors of exposure intensity at the population level, we empirically model exposure intensity using a fixed effects linear model fitted using weighted least squares. Predictor variables tested focus on demographic, geographic, and temporal influences on activity behavior and climate. Exposure is non-normally distributed; therefore, we choose the best performing model that predicts logarithmic, daily MDMs for ATUS respondents who spent any time outdoors above 27 °C T_A. The relationship of interest focuses on categorical demographic indicators for age group, gender, household income, and race with additional indicator variables to control for climate zone, geographic region (MSA), calendar date, and season. This relationship is modeled as:

$$log\ (MDM_{i,c,d,m,s}) = \beta_A Age + \beta_G Gender + \beta_I Income + \beta_R Race + \gamma_{c,d,m,s} + \epsilon_{i,c,d,m,s} \tag{1}$$

where i represents the individual, c represents the climate zone, d represents the calendar date, m represents the MSA, and s represents season. The demographic terms (e.g. *Age*, *Gender*) represent a vector of categorical indicators with corresponding coefficients for each subgroup level (e.g. β_{A1} for age group 1; ages 15–24). The Term $\gamma_{c,d,m,s}$ represents a matrix of indicator variables included to control for unobserved effects across the spatiotemporal indicators (climate, date, MSA, and season). To further control for intra-MSA and intra-season correlation, standard errors are clustered on both the MSA and the season. A weighted least squares approach is utilized to incorporate the ATUS individual-level weights to adjust for non-response, strata over-sampling, and response variance (US BLS and US CB, 2017).

With time-use data, meteorological data, and activity intensity data combined, we compare aggregated exposure patterns across activity types, demographic groups, and cities. We evaluate environmental exposure across major activity types (work, travel, household, etc.). These activity groupings by type are simplified from the ATUS coding and allow for simple differentiation across relevant outdoor activities.

3. Results

Over the 11.5-year sample period, 73,121 respondents engaged in 1.42 million total activities across the 50 examined MSAs. We estimate 3,486 respondents engaged in 6,666 activities outdoors above the 27 °C T_A threshold in this sample, totaling 6,302 hours, or 0.36% of all observed activity time in the sample period. Results are primarily presented in MET-degree-minutes (MDMs) above 27 °C T_A and activity intensity-time (MET-minutes) above 27 °C T_A to examine the combination of heat exposure and activity intensity across urban populations. The mean person-day outdoor exposure for all individuals engaging in at least one activity above 27 °C T_A is 415 deg-min above 27 °C T_A, and

Table 1
Summary results for fixed effects model predicting daily exposure intensity for respondents who engaged in outdoor activities above 27 °C T_A. Predicted percent increase in daily MDMs is estimated by transforming regression coefficients using $(e^{\beta} - 1)*100\%$.

Variable	Predicted % increase in daily MDMs	*p*-value
Age (control: 35 − 44, n = 721)		
15–24 (n = 401)	2.85% (−22.7%, 36.8%)	0.847
25–34 (n = 541)	−19.2% (−27.3%, −10.3%)	< 0.001
45–54 (n = 622)	16.2% (−4.05%, 40.7%)	0.124
55–64 (n = 513)	−4.63% (−24.4%, 20.4%)	0.690
65+ (n = 688)	29.5% (2.49%, 63.6%)	0.0304
Gender (control: Male, n = 1746)		
Female (n = 1740)	−36.5% (−46%, −25.4%)	< 0.001
Household Income (control: $50,000 – $74,999, n = 617)		
< $15,000 (n = 470)	15.7% (0.314%, 33.4%)	0.0453
$15,000 - $29,999 (n = 551)	−3.07% (−14.9%, 10.4%)	0.639
$30,000 - $49,999 (n = 695)	1.94% (−19.9%, 29.8%)	0.876
$75,000 - $99,999 (n = 432)	−1.39% (−18%, 18.6%)	0.882
≥ $100,000 (n = 721)	4.96% (−37%, 74.8%)	0.852
Race (control: White, n = 2813)		
Asian (n = 112)	−51.1% (−77.5%, 6.68%)	0.0724
Black (n = 489)	−34.2% (−46.2%, −19.5%)	< 0.001
Other / Mixed Race (n = 72)	35.7% (−10.4%, 106%)	0.150
Multiple R^2: 0.627; Adjusted R^2: 0.349		

the mean person-day exposure intensity is 1,581 MDMs above 27 °C T_A. Summaries of population, total activities, outdoor activities, and temperatures by MSA can be found in SI Table S2.

3.1. Outdoor heat exposure and activity intensity by demographics

Heat exposure intensity per person per day varies across demographic groups with at least one subgroup in each demographic indicator being significant at the $p = 0.05$ level. When controlling for other factors, we estimate females had 36.5% less intense exposure than males (CI: −46.0%, −25.4%; $p < 0.001$). Those identifying as Black race had 34.2% less intense exposure (CI: −46.2%, −19.5%; $p < 0.001$) compared the control (White), while Asian and other races were not significant. Two of five age groups were found to be significant: the elderly (ages 65 and over) accumulate 29.5% more exposure intensity (CI: 2.49%, 63.6%; $p = 0.0304$) relative to the control group (ages 35–44), while young adults (ages 25–34) accumulate 19.2% less exposure intensity (CI: −27.3%, −10.3%; $p < 0.001$) relative to the control group. Table 1 summarizes the results of model. Fig. 3 shows activity intensity-time for three of the significant demographic comparisons across NWS heat index thresholds, displaying trends of differing exposure between relevant demographic groups.

The activity "lawn, garden, and houseplant care" is the most significant activity that contributes to total population exposure above 27 °C T_A, and it is the main factor of higher elderly exposure: 46% of total exposure intensity above 27 °C T_A among the elderly are during "lawn, garden, and houseplant care" compared to only 30% of exposure intensity for the non-elderly population. This discrepancy of time spent engaging in plant-related care is also a component of lower exposure in the Black population; only 25% of outdoor activities above 27 °C T_A are plant-related care compared to 30% for non-Blacks. It should be acknowledged that the 'houseplant care' portion of this activity would occur indoors, while 'lawn and garden care' would occur outdoors. Despite houseplant care occurring indoors, we argue it accounts for a minimal portion of the total exposure. The median activity duration of "lawn, garden, and houseplant care" occurring above 27 °C T_A is 60 min. If we assume *every* "lawn, garden, and houseplant care" activity dedicated an average of 5 min of the total activity time to (indoor) 'houseplant care' with all remaining time dedicated to (outdoor) 'lawn & garden care,' 95% of the total outdoor exposure would still be attributed to 'lawn & garden care.' If instead *every* instance of the activity dedicated an average of 20 min to 'houseplant care,' 79% of total outdoor exposure would still be attributed to 'lawn & garden care.' Therefore, we believe 'houseplant care' does not significantly affect the trends in outdoor exposure as it is appears unlikely that individuals caring for houseplants would take up a significant amount of time indoors relative to the outdoor portions of 'lawn and garden care.'

Less time spent working is casually related to an increase in exposure as individuals may choose to speed more time engaging in outdoor leisure and discretionary activities. We define discretionary activities as activities where postponing or altering the time of occurrence is largely driven by personal preference. For example, one factor that contributes to lower exposure in young adults is an elevated time spent working compared to other age groups. For individuals engaging in at least one outdoor activity above 27 °C T_A, young adults (ages 25–34) spent 23% more time engaged in work-related activities than all other individuals. The reverse is true in the elderly who spend more time engaging in leisure activities due to a large majority of individuals age 65 and over being retired or working less than full time. As a result, elderly exposure is slightly elevated compared to young populations. Additionally, heat exposure on weekends is higher relative to weekdays due to less individuals engaging in work-related activities on weekends (see SI Fig. S1).

3.2. Outdoor heat exposure and activity intensity by activity type

Discretionary activities (e.g. gardening, sports) dominate high urban outdoor heat exposure as opposed to non-discretionary activities (e.g. care for others, civic obligations). Fig. 4 shows outdoor heat exposure time by activity type across the 50 studied major US urban areas. Exposure above 27 °C T_A most commonly occurs during the discretionary activities "lawn, garden, and houseplant care" (18% of total outdoor activities), and "walking for exercise or leisure" (5.4% of total outdoor activities). Outdoor travel, which may be less discretionary depending on purpose (e.g. travel for work is less flexible while travel for leisure is more flexible), is the most frequent activity type to acquire heat exposure above 27 °C T_A (37% of all activities). However, because travel durations are often short (the 90th percentile outdoor travel time is 20 min), total exposure from travel is lower than other activities.

As heat approaches extremes, there are a smaller number and a smaller proportion of individuals engaging in outdoor activities. This decrease results from both decreased frequency and decreased duration of outdoor activities, most notably for activities of typically longer durations or higher intensities (e.g. activities occurring in the top quantile in Fig. 4). Because outdoor activities are not frequently observed at extreme temperatures, and extreme temperatures are rarely reached even in the hottest climates, 'extreme' outdoor heat exposure observed via the ATUS is rare. Despite this rarity, there are still many observations of potentially high-risk activities during high temperatures; we observed 719 outdoor activities above 27 °C T_A that occurred above the 90th percentile exposure intensity (2,563 MDMs > 27 °C T_A). If we apply the individual-level survey weights to estimate the total population surpassing this threshold on a hot summer day, this would be equivalent to approximately 12 million people across the 50 studied MSAs (6.7% of the 2016 MSA populations).

3.3. Heat exposure by urban region and climate

Heat exposure is partially driven by region and climate; comparing exposure across the MSAs indicates that urban populations experience different cumulative daily exposure during days with T_A above 27 °C. Personal daily MDMs above 27 °C T_A for 39 of the studied MSAs are

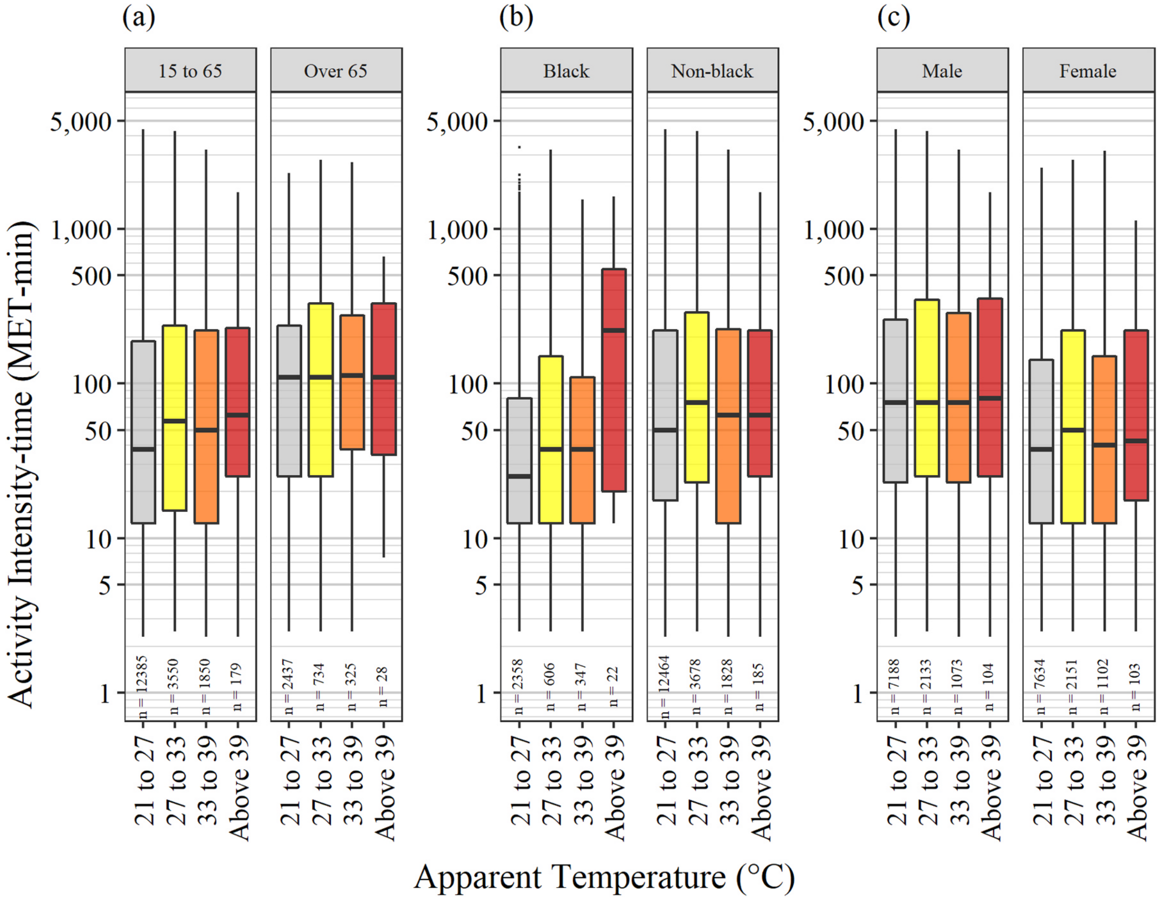

Fig. 3. Weighted outdoor activity intensity-times for significant demographic groupings of elderly ages vs. non-elderly ages (a), Black race vs. non-Black race (b), and gender (c) under different heat thresholds for the 50 studied MSAs. Note that the y-axis scales logarithmically. Boxplots are for the interquartile range (IQR) and lines/dots extend to the minima and maxima. T_A ranges 21–27 °C represent a baseline, 27–33 °C represent heat index warning 'caution,' 33–39 °C represent heat index warning 'extreme caution,' 39 °C and above represent heat index warnings 'danger.' The number of outdoor activities for each grouping is given by 'n' at the bottom of the figure.

displayed in Fig. 5 (MSAs with less than 30 samples are not displayed; for more detailed results, including all MSAs studied, see SI Table S7). Individuals in southern US MSAs more commonly experienced higher daily exposure intensities with New Orleans, LA and Birmingham, AL having the highest median and mean MDM per day, and the most extreme case of exposure intensity occurred in Phoenix, AZ.

Despite climate being a significant predictor in exposure, it is clear that other factors across MSAs contribute to varied regional exposure. In model evaluation, we included measures of regional sprawl (MSA sprawl index via Hamidi and Ewing, 2014) to evaluate if urban form is a predictor of exposure intensity. When controlling for geographic region as a random effect in mixed effects models, MSA sprawl was found to be a statistically significant but very low magnitude predictor. Therefore, we conclude that sprawl was not a significant influence on exposure intensity across the measured urban population, but future work should explore additional urban form metrics to improve understanding of inter-urban influences on extreme exposure.

4. Discussion

Few studies have investigated the effect of hot days on outdoor activity at the level of the individual. Understanding individually experienced heat exposure during activities is difficult for many reasons: difficulty in obtaining a large sample size (especially for the most extreme temperatures); low spatial or temporal resolution in temperature data (especially in urban microclimates); and low spatial or temporal resolution activity data. Some previous research has evaluated the effect of temperature on personal activity and behavior using survey data. Obradovich and Fowler (2017) estimated change in likeliness to be physically active in a month and found that individuals in the US typically become less active as temperature reaches extremes. Zivin and Neidell (2014) estimated change in average time spent outdoors due to temperature, finding that less time is spent outdoors for days with more extreme temperatures. However, these studies focus on monthly and daily summary temperatures rather than individually experienced temperatures during activities and do not estimate personal heat exposure. This study improves our understanding of individually experienced heat exposure for a large, heterogeneous population sample and identifies disparities in accumulated heat exposure.

Various demographic subgroups such as those in poverty or the elderly are often cited as more vulnerable to heat stress due to reduced access to cooling, and in some cases, race has also been linked to increased negative heat-related health outcomes (Eisenman et al., 2016). These results provide further evidence of heat-vulnerability in low-income and elderly individuals as we find they accumulate higher exposure intensity when controlling for other factors. On the other hand, black individuals have lower exposure intensity than other races despite often having higher rates of heat-related morbidity and mortality compared to the general population. Males were found to accumulate more heat exposure relative to females, and males are observed to engage in activities during hot weather more often than females (54% of males engaged in outdoor activities when temperatures are above 27 °C T_A versus 46% of females). This agrees with past research that indicates males are exposed to heat more than females and may be at more risk

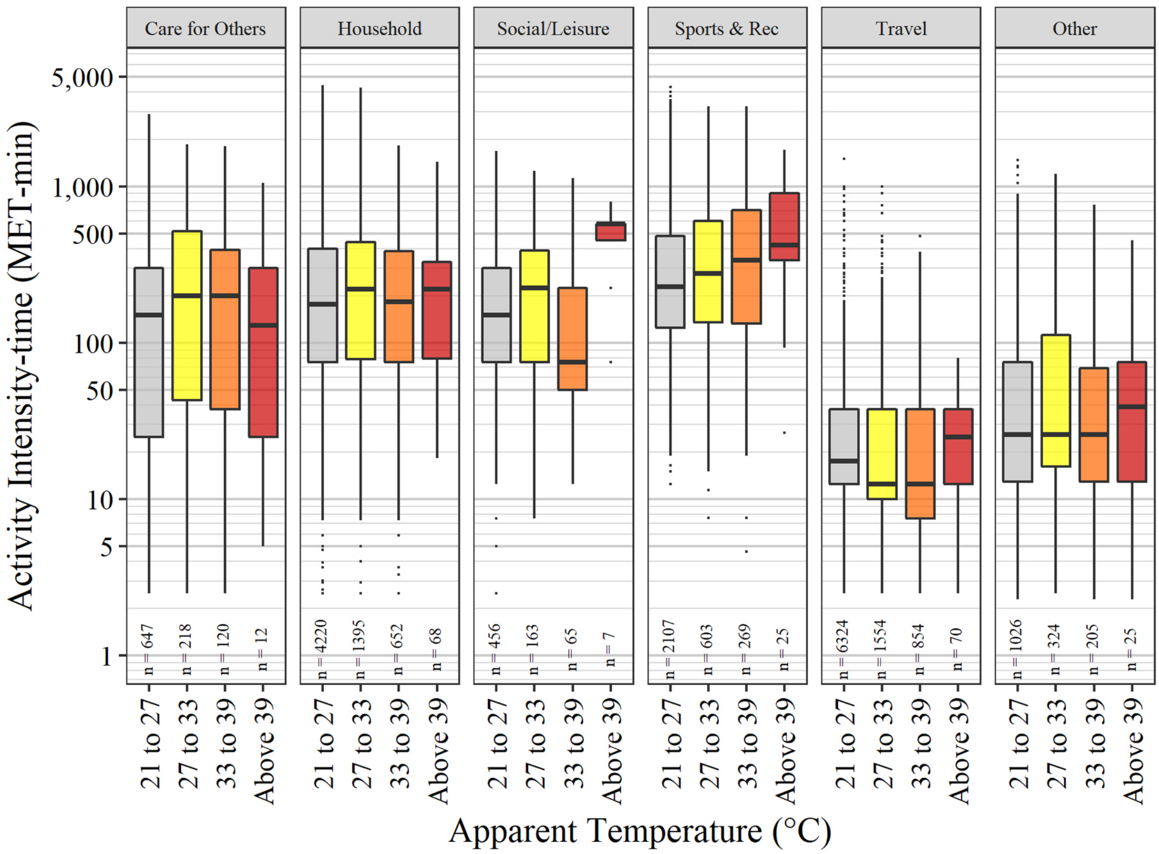

Fig. 4. Weighted outdoor activity intensity-times by activity type and heat thresholds for the 50 studied MSAs. Note that the y-axis scales logarithmically. Boxplots are for the IQR and lines/dots extend to the minima and maxima. T_A ranges 21–27 °C represent a baseline, 27–33 °C represent heat index warning 'caution,' 33–39 °C represent heat index warning 'extreme caution,' 39 °C and above represent heat index warnings 'danger.' The number of outdoor activities for each grouping is given by 'n' at the bottom of the figure. 'Work' activities are excluded due to very low sample size. Activities in the 'Other' category include personal care, education, consumer purchases, giving and receiving services, civic obligations, eating and drinking, religious activities, volunteering, and telephone calls.

(Kovats and Hajat, 2008). Although the most extreme exposure cases may be atypical and uncharacteristic of a demographic cohort, outdoor heat exposure and activity intensity quantified in this study (excluding work-related activities) are not solely sufficient to explain heat-related health outcomes.

Climate acclimatization and abnormally hot periods relative to typical regional weather may increase heat exposure especially if individuals engaging in moderate to high intensity activities do not reduce their activity time or physical activity intensity. After heat waves, individually perceived thermal comfort may increase due to short-term acclimatization (Lam et al., 2018). In this study, we used an absolute, fixed temperature threshold across all cities to quantify how exposure varies across cities or population groups. Future work might extend this approach to consider city-specific temperature thresholds derived as a function of local climatology, to account for possible regional acclimatization in activity patterns and/or health risks (e.g., Anderson and Bell, 2009; Grundstein et al., 2015). Although heat exposure may be perceived as more severe in hotter and more humid regions, outdoor heat exposure for some individuals may be comparable across regions with varied climates. This also further highlights the potential threat of increased severity and intensity of heat waves on unacclimated individuals (e.g. tourists, visitors), and individuals living in areas with less access to cooling infrastructure. However, the issue of smaller samples of extreme exposure in temperate and colder climates persists, limiting our understanding of extreme heat exposure in these regions despite continued warming in cities (McCarthy et al., 2010; Mora et al., 2017).

The inclusion of activity intensity (metabolic equivalent of task) allows for additional perspective in assessing heat exposure. In this analysis, the contrasts in heat exposure intensity (MDMs) among subgroups are primarily driven by the contrasts in heat exposure. Contrasts in physical activity intensity are only significant between men and women (males: 5.50 mean MET above 27 °C T_A; females: 5.14; $p < 0.001$). Although variation in MDMs is mainly driven by apparent temperature and exposure duration, we consider it important to evaluate heat exposure as a function of environmental heat, activity duration, and activity intensity to identify all causal factor that may influence the intensity of personal heat exposure. This is especially important in understanding extreme and atypical cases of exposure. Future work should explore the relationship between heat exposure, activity intensity, and health outcomes to better understand the role of physical activity intensity in heat-related health outcomes.

4.1. Limitations

The approach in this analysis and the nature of the survey data inherently limits our ability to fully understand urban outdoor activity exposure. In particular, important elements not captured in the ATUS are outdoor work, omission of homeless individuals, and potential sampling biases. Additionally, outdoor thermal conditions are heterogeneous within a MSA, but only one meteorological station was used per MSA.

Heat exposure among working people is a very important global concern (Kjellstrom et al., 2009), but the ATUS is poorly structured to evaluate individual level heat exposure in occupational settings. To assess heat exposure during work more accurately, more robust survey data are required that closely monitor activity intensity and duration. The ATUS coding limits the ability to determine if work related

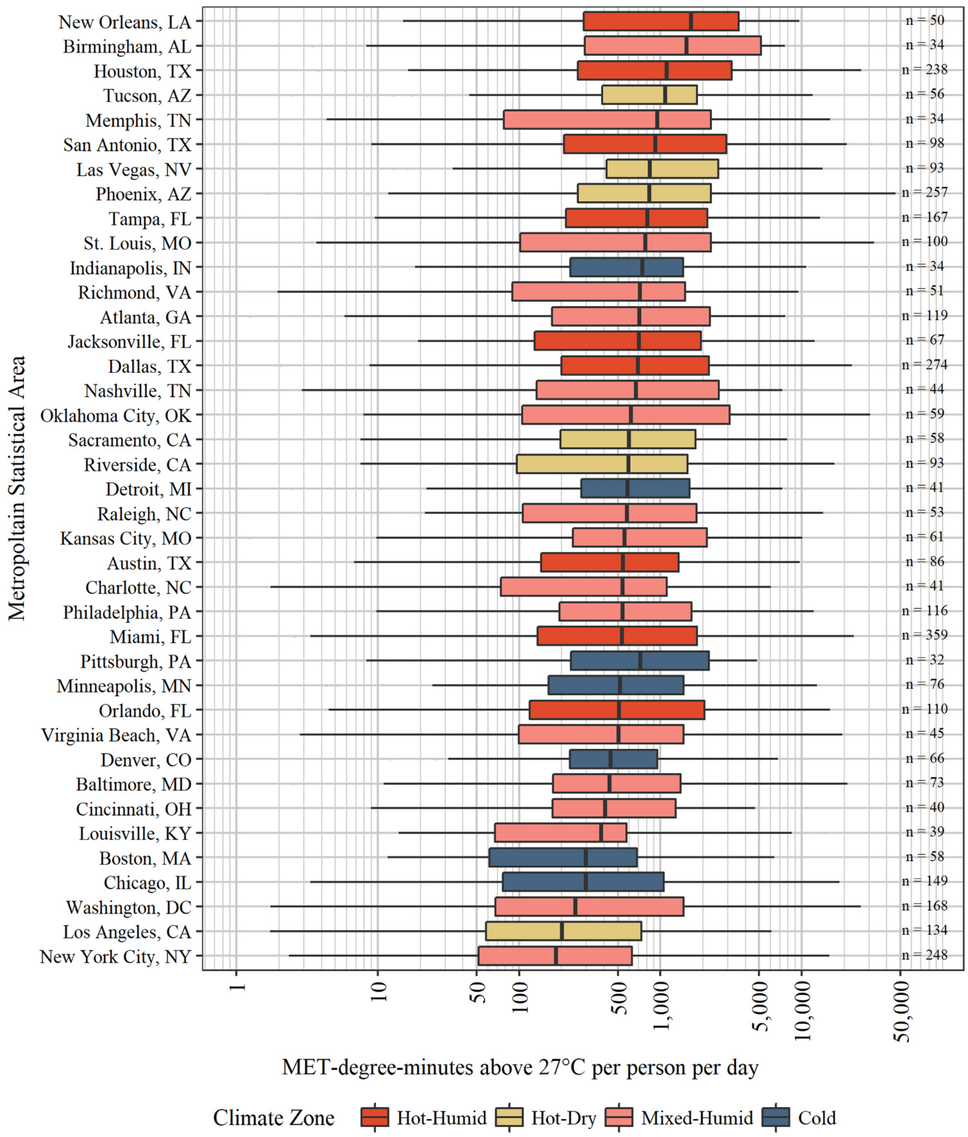

Fig. 5. Personal daily outdoor MET-degree-minutes (above 27 °C T_A) for 39 of the most populated Metropolitan Statistical Areas. Note the x-axis scales logarithmically. Only MSAs with exposure significant at p = 0.05 are retained. Boxplots are for the IQR and lines/dots extend to the minima and maxima. All individuals in an MSA that reported at least one outdoor activity above the 27 °C T_A threshold are included. On the right of the figure, the number of person-days or each MSA is given by 'n.'.

activities occurred outdoors; only 0.47% of work related activities were confidently coded as outdoors, regardless of temperature. As a result, samples of outdoor work may significantly under represent outdoor workplace behavior because ATUS reporting options obfuscate indoor versus outdoor presence during work. If work occurred outdoors and away from the respondent's household, a more appropriate response to location could arguably be "outdoors away from home" instead of "at the respondents workplace." Zivin and Neidell (2014) identify certain industries as more vulnerable to high temperatures, and Eisenman et al. (2016) correlated higher mortality risk for industries with higher rates of outdoor work, but there is little knowledge on the frequency of high heat outdoor work itself.

The ATUS inherently excludes homeless individuals, as it is a household study. Heat-related morbidity and mortality among the homeless can be disproportionately higher due to extended time outdoors in the heat (Yip et al., 2008) along with other exacerbating factors related to health status and access to healthcare. Quantifying urban heat exposure in the homeless population is vital, but it must be done using different approaches.

Biases in survey response rates may prevent researchers from fully understanding total population heat exposure via survey data. Between 2004 and 2015, the ATUS survey response rate was 54% (US BLS and US CB, 2017). Regarding sampling bias, Abraham et al. (2006) found certain subsets of individuals are more likely to reject participation in the ATUS (e.g. higher education and income individuals have higher response rates). However, their analysis focused only on the second survey year of data (2004) in the middle of which the survey methodology was changed. The use of ATUS person-level weights in this analysis should minimize these sampling biases as they correct for non-response, but we acknowledge that some unrecognizable biases may arise and under-represent exposure for certain sub-populations or activities. We caution the development of local policies and intervention programs without more detailed consideration of the sampling limitations. One other minor sampling limitation in this analysis is the banding of activity times. This occurs because activities are reported as 'round' or 'convenient' as respondents do not record exact durations but only estimate them after the activities have occurred (e.g. respondents most commonly report time spent traveling as 15, 30, or 45 min).

Throughout an urban region, individually experienced temperatures can vary due to complex microclimates and heterogeneity of urban

form (Hart and Sailor, 2009; Kuras et al., 2015; Middel et al., 2014, 2016, 2017; Stewart and Oke, 2012). To test sensitivity of personal exposure due to varied urban climates, weather data inputs were varied for the Los Angeles MSA - a large geographic metropolitan area with diverse microclimates. Exposure patterns did not appear to change significantly, but sample sizes did decrease with use of more coastally located meteorological stations. Use of coastal temperatures (Los Angeles International Airport, 2 miles from coast) reduced the observed number of outdoor activities above 27 °C T_A to 0.8% of all outdoor observations (n = 5,022). Conversely, when using observations further inland (Ontario International Airport, 35 miles from coast), 12% of outdoor activities would be classified above 27 °C T_A. This however, is an extreme example; most regions (especially non-coastal regions) have far less variation in temperatures, and inter-MSA temperature variations may have negligible impacts on time use (Zivin and Neidell, 2014).

Although this study does not consider indoor heat exposure, indoor environments can also play a significant role in accumulated heat exposure at the individual level (Quinn et al., 2014; White-Newsome et al., 2012). Coastal and temperate urban regions can have vastly different air conditioning (AC) penetration than regions with more uniform heat. In 2015, only 53% of urban households in the Marine climate zone had any AC while 94% of households in Hot-Humid climates had any AC (US EIA, 2015). Fraser et al. (2016) assessed differences in AC penetration between Los Angeles and Phoenix and found that approximately 95% of metropolitan Phoenix households had central AC while “less than 50%” of households in Los Angeles had central AC. Additionally, lower income households are less likely to have adequate cooling alternatives (US EIA, 2015), making it more difficult to cool off.

5. Conclusion

With the threat of increased severity and frequency of extreme heat events and subsequent adverse impacts on the health and well-being of urban residents, improvements in the strategies that cities use to mitigate and adapt to heat are needed. We contribute to the improvement of heat response policies and initiatives with new evidence concerning the drivers of urban outdoor heat exposure in the contiguous US and variability across cities and demographic groups. Using the ATUS, we found that many outdoor activities occur in US cities under conditions deemed hazardous to human health based on the heat index. Discretionary activities were a substantial contributor to exposure under high heat conditions. Inter-city comparison of aggregated personal exposure metrics revealed that cities with the most extreme temperatures do not necessarily have the highest outdoor heat exposure. Although heat exposure can vary significantly person-to-person, disproportionately high heat exposure is not necessarily exhibited in groups known to be at higher risk of adverse heat-health outcomes. Overall, the results highlight how diversity of activity types, demographic groups, and geographic regions can significantly vary outdoor urban heat exposure. Continued work in estimating heat exposure at the individual level is needed; there are still gaps in understanding how (and at what level) heat exposure for an individual could translate to increased risk for negative heat related health outcomes. More refined, spatially explicit analysis of exposure patterns and microclimate variability within cities can help provide a clearer perspective of the circumstances, people, and places where targeted mitigation and adaptation strategies will be most effective.

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Competing financial interests

The authors declare no competing financial interests.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.healthplace.2018.08.014.

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